A New Mother Wavelet for Fetal Electrocardiography, to Achieve Optimal Denoising and Compressing Results

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Abstract

A real- time, denoise, and compress algorithm based on the wavelet transform (WT) for abdominal electrocardiograms (AECG) signals is designed. In this study an algorithm is designed which achieves an AECG with minimal noise and high compression rate (66.7%) while keeping the AECG quality at a clinically acceptable level. This is done at the first stage before extracting the fetal electrocardiogram (FECG) from the AECG.

A new mother wavelet (MW) is especially designed for AECG analysis. No complex low- and high- pass reconstruction and decomposition filters, with (bi)-orthogonal properties, are needed as is traditionally the case. The algorithm can also be used to design a MW for other purposes. The algorithm is evaluated by AECG data from the Database for the Identification of Systems (DaISy) showing low MSE (<<1.2%), RMS (<<0.016 μVolt), and excellent visual similarity between the original and the reconstructed AECG.

1. Introduction

Recently, high-risk pregnancies are becoming more prevalent. Twenty percent of all pregnancies are complicated by preterm delivery, fetal growth retardation, or hypertension. Therefore, the state of the fetus must be carefully and frequently monitored to intervene promptly when necessary. The currently available technique for monitoring mother and fetus, cardiotocography (CTG), has limited predictive value, suffers from subjective assessment of the obtained records, and is not very well suited for 24-h and at-home monitoring. An interesting non-invasive method is to monitor the fetal electrocardiogram (FECG). Important issues are denoising the FECG, data compression, fast data transmission to guarantee real-time communication and low transmission costs.

In the past few years, much work has been done in ECG signal denoising/compressing using wavelet transforms (WT) with excellent performances compared with standard techniques [1, 2]. The WT meets the ability of high compression without losing clinically important data, is fast enough to guarantee real-time monitoring, and can easily be programmed in a microprocessor or FPGA for use in at-home monitoring. Other methods that have been developed are noise cancellation [3], multi-channel singular value decomposition [3], adaptive filtering technique [4], blind source separation [4, 5], and singularity detection with wavelets [1, 6].

Unfortunately, measurements techniques are not so far yet to measure FECG non-invasively with a high signal-to-noise ratio. Only invasive methods exist, by placing electrodes on the fetal scalp during childbirth. Instead of this, the electrocardiogram at the abdomen (AECG) is measured by placing electrodes on the maternal abdomen. The AECG is a linear superposition of the FECG and the electrocardiogram of the mother's heart: the maternal electrocardiogram (MECG). An additional algorithm, not included here, must be developed to extract the FECG out of the AECG. Problems occur, since the FECG has a normal maximum QRS amplitude in the range of 10 to 50 μVolt[1] [6, 7] much lower than the MECG, which has a normal maximum QRS amplitude of 1600 μVolt [8]. At a further stage, the FECG can be extracted from the AECG by measuring the maternal heart rate (MHR) and applying filters to remove the maternal QRS complex.

This paper presents an algorithm based on the WT to denoise and compress the AECG without losing significantly mathematical or visual (medical) information. An important stage in WT, is constructing a function, called the mother wavelet (MW), which is preferable to have a shape similar to the AECG. Higher compression is achieved when more correlation exists between the MW and the transformed signal into wavelet coefficients. Although a great number of MWs exist, little or no literature exists about MWs having a similar shape as an AECG or ECG. Instead, other existing MWs are used when transforming the AECG into wavelet coefficients.

This study constructs a new MW, called AECG MW, with significantly better performances than MWs before.

[1] Experimental results from week 24 to week 39 of gestation

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In this paper, first the WT is derived for the new MW. Then the new WT is designed. Finally, an algorithm is presented which calculates the wavelet coefficients.

2. Proposed algorithm

In this section, first, the WT is explained that shows compression and denoising properties. Secondly, the AECG MW is presented. Finally, an algorithm is designed to identify the parameters of the MW.

2.1. Wavelet transform

The Continuous Wavelet Transform (CWT) [9] is defined as the sum over all times of the continuous signal *f(t)* multiplied by scaled, shifted versions of the MW $\psi((t-\tau)/s)$ as shown in (1).

$$CWT(s,\tau) = \frac{1}{\sqrt{s}} \int f(t)\psi\left(\frac{t-\tau}{s}\right)dt \quad (1)$$

The parameter s is the scale factor that compresses or stretches the MW and τ is the translation of the MW along the time axis.

The CWT can be considered as a correlation of *f(t)* with the MW, stretched or contracted by the scale factor s and considered at time lag τ. Higher correlation exists if *f(t)* and the MW show higher similarity, presenting less information in the other wavelet coefficients of the CWT and more information in the MW. Since the MW is known by the receiver, only the wavelet coefficients are transmitted. This property is used in compressing the AECG.

The signal *f(t)* is represented by coefficients $\gamma(s, \tau)$ multiplied by the MW, scaled by the scale s and translated by τ. This representation is shown in (2).

$$f(t) = \int\int \gamma(s,\tau)\psi\left(\frac{t-\tau}{s}\right)d\tau ds \quad (2)$$

The Discrete Wavelet Transform (DWT) is defined by splitting *f(t)* into smaller non-overlapping parts $f_i(t)$, taking a finite number of scales N ($j=N$, $k=N$), and downsampling ($\Downarrow$) the discrete wavelet coefficients with N to reduce the number of wavelet coefficients samples to M, the number of samples of $f_i(t)$, as shown in (3).

$$DWT_i(s,\tau,N) = \left\langle \sum_{j=1}^{N}\sum_{k=1}^{N} CWT_i(s_j,\tau_k)\right\rangle \Downarrow N \quad (3)$$

The inverse discrete wavelet transform (IDWT) is shown in (4) where $f_{r,i}[t]$ is the reconstructed $f_i(t)$ signal.

$$f_{r,i}[t] = \sum_{j=1}^{N}\sum_{k=1}^{N} \gamma_{j,k,i}[s_j,\tau_k]\psi\left(\frac{t-\tau_k}{s_j}\right) \quad (4)$$

2.2. AECG mother wavelet

The normal AECG is constructed by a linear superposition of the normal MECG and normal FECG and sampled at 500Hz as recommended by the American Heart Association and used as standard in Hospitals. The QRS and T waves of the MECG and the FECG are simulated by an algorithm based in part on [10], originally created by [11], and further modified in this study.

The normal values used for modelling the MECG and FECG are the means of the values shown in Table 1 and 2.

TABLE 1
NORMAL MECG VALUES [8, 12]

	Amplitude (μV)	Width (s)
QRS	1600	0.07-0.11
T	100-400	0.18
QT		0.38-0.44

TABLE 2
NORMAL FECG VALUES [13-15]

	Amplitude (μV)	Width (s)
QRS	10-50	0.02-0.05
T	0-0.35·*QRS*	0.09-0.14
QT		0.16-0.29

The normal MHR is between 60-100 beats per minute (BPM) [6]; the normal fetal heart rate (FHR) is between 120-160 BPM [13]. The MECG and FECG are modelled with the mean value of MHR and FHR, respectively.

As stated earlier, the MW is preferable to have a shape similar to the AECG. The AECG consists of a maternal QRST complex (4 peaks) and a fetal QRST complex (4 peaks). A Gaussian can be used to model the peaks in the AECG since a Gaussian is symmetric around its mean, gains its maximum value at the mean and goes very fast to zero, similar to a peak. Hence, a Gaussian interferes minimally with other Gaussians and therefore all peaks of the AECG can be modelled by summing up a minimum of 8 Gaussians. The conditions of being a MW are satisfied by taking as MW the normalized normal AECG for positive time (t>0) and the negative (*-1) normalised normal AECG for negative time (t<0) and centering the resulting waveform at zero time.

2.3. Parameters s_j, τ_k and $\gamma_{j,k,i}[s_j,\tau_k]$

In this section, the parameters s_j, τ_k, and $\gamma_{j,k,i}$ $[s_j,\tau_k]$ are identified. For s_j, discrete positive integer values are chosen, since s_j is the scale factor and no restrictions exist. The other wavelet coefficients are identified using the autocorrelation of the MW and reducing the row echelon form of a VxV matrix using V AECG samples.

3. Results and discussions

In this section, experiments are described to evaluate several AECG MWs and to compare the best one obtained existing MW from the Matlab wavelet toolbox.

The difficulty in evaluating and comparing this method with others is that no general AECG database exists. Previous researches refer to own acquired data. A nearly new database called DaISy [16] contains AECG recordings from one pregnant woman from 5 different positions during 5 seconds.

The AECG MW is calculated for different scale levels. A maximal scale level of 5 is used, to avoid excessive processing time needed in calculating τ_k for a higher scale level. The MWs are evaluated using the MSE and the RMS. Also a visual comparison is performed between the original and the reconstructed signal.

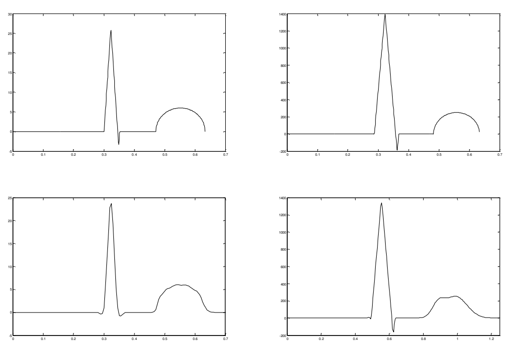

Fig. 1: Normal FECG (Top left), Normal MECG (Top right), mnFECG (Down left), and mnMECG (Down right)

In Fig. 1 the original normal FECG and the modelled normal mnFECG (left) and the original normal MECG and the modelled normal mnMECG (right) are shown, both with 8 Gaussians, with excellent visual similarity. Moreover the mnFECG and mnMECG are smoother than the original signals, as in real-life situations. Using more Gaussians will probably show better visual results but increasing complexity and processing time. Excellent modelling is also confirmed by a RMS of 0.324 µV and a MSE of 0.55% for the mnFECG and a RMS of 9.532 µV and a MSE of 0.13% for the mnMECG. Combining the Gaussians of both mnFECG and mnMECG yields the desired modelled normal AECG (mnAECG).

The AECG MW is designed using only the model of the mnMECG to avoid excessive processing time in calculating τ_k, since the superposition of the mnFECG and the mnMECG involves 16 Gaussians. The mnFECG can be shaped by the mnMECG, due to the fact that the mnFECG and mnMECG have similar shapes and comparable proportions, and that the WT has the property of compressing, stretching, and scaling a MW. Hence, superposition of the mnFECG can be omitted. However, it is interesting to introduce this model in a future study. Further the obtained MW is refined to satisfy the condition of being a MW.

The evaluation of the AECG MW is done with normalized AECG data from DaISy (4th dataset: 4.75-5.00s) [16]. The results are shown in Table 3 where the column 'fit MECG / FECG' contains information about the visual similarity between the original and the reconstructed MECG / FECG peaks, where 'ok' means good AECG reconstruction, 'peak' means bad reconstruction of the AECG peaks, and 'place' means bad reconstruction of the location of the AECG peaks.

TABLE 3: EVALUATION OF THE AECG MW USING DIFFERENT SCALE LEVELS

Scale level	MSE (%)	R MS (µV)	Fit MECG	Fit FECG
1	0	0	ok	ok
2	0.24	0.010	ok	ok
3	0.96	0.020	ok	ok
4	1.5	0.025	peak	peak
5	7.3	0.054	ok	peak, place

The AECG MW with scale level 3 has still good visual similarity and has a low MSE and RMS. Table 4 shows similar results from DaISy (4th dataset: 3.50-4.00s) [16].

TABLE 4: EVALUATION OF THE AECG MW USING DIFFERENT SCALE LEVELS

Scale level	MSE (%)	RMS (µV)	Fit MECG	Fit FECG
1	0	0	ok	ok
2	0.38	0.008	ok	ok
3	1.2	0.016	ok	ok
4	3.0	0.025	peak	peak (a bit)
5	6.8	0.037	peak (a bit)	peak, place

In Fig. 2 the original and reconstruction plots are shown of the last dataset used, using the AECG MWs with scale level 3.

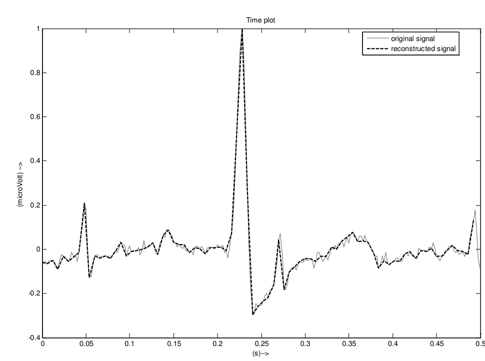

Fig. 2: Original and reconstruction signal with data from DaISy [16]

The last experiment consists of comparing existing MWs (scale level 3) with the AECG MW with scale level 3. The results are shown in Table 5 using the same data as used for Table 4. The existing MWs perform better than the AECG MW with scale level 3. The AECG MW could perform better if: 1) τ_k is calculated at maximal resolution, 2) the AECG signal is modelled by using the model of the mnMECG with more than 8 Gaussians, 3) the AECG signal is modelled by using the superposition of the mnFECG and the mnMECG. (It is also interesting to use mnFECG and mnMECG models with each summation of more than 8 gaussians), 4) the AECG signal is sampled at a higher rate.

TABLE 5: EVALUATION OF EXISTING MWs USING DIFFERENT SCALE LEVELS

Mother wavelet	MSE (%)	RMS (μV)
Haar	6.72e-4	0.0050
Daubechies 7(db7)	7.31e-4	0.0052
Biorsplines 3.9 (bior3.9)	7.10e-4	0.0051
Reversebior 3.9 (rbio3.9)	9.97e-4	0.0060
Coiflets 5 (coif5)	7.12e-4	0.0051
Symlets 8 (sym8)	7.00e-4	0.0051
Dmeyer (dmey)	97.93e-4	0.019

Another point for future study is applying an appropriate threshold selection rule on the data [17], which can increase the compression rate.

4. Conclusions

This paper presents a denoise and compression algorithm for AECG signals based on wavelet transforms. In the first part, a general method to design a MW based on wavelet high correlation is designed. An AECG MW is proposed with the ability to reconstruct several AECG signals with a maximum MSE of 1.2%, a maximum RMS of 0.016μV, and an excellent visual match with the original, without applying a threshold selection rule.

The algorithm used guarantees real-time monitoring of an AECG signal, since the wavelet coefficients are calculated with a fixed delay of V samples multiplied by the AECG sample frequency and by a variable negligible delay (~ linear to the length of the AECG signal). Hence, the algorithm can be implemented by a chip which has the ability to produce accurate and fast reduced row echelon forms of the transformed signal.

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